Lending Intensity, Funding Composition, and Liquidity Risk Persistence in Sri Lankan Commercial Banks: A Dynamic ARDL Analysis

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Abstract

This study examines the dynamic effects of lending intensity and funding composition on liquidity risk persistence in Sri Lankan licensed commercial banks, using monthly balance sheet data spanning December 1995 to November 2024 and an autoregressive distributed lag framework. Employing an autoregressive distributed lag (ARDL (2,2,1,2) framework, the study captures short-run adjustment dynamics of lending intensity, borrowing dependence, and loan growth on liquidity risk. Unit root tests confirm all variables are integrated of order one I(1), validating the ARDL approach. The bounds cointegration F-test (F = 0.923) does not confirm a long-run equilibrium relationship over the full sample, a finding attributed to parameter instability identified by the CUSUM test (Figure 1, S = 5.560, p < 0.001), reflecting structural changes in Sri Lanka's banking and regulatory environment over the sample period. Short-run results reveal that liquidity risk is highly persistent, with AR coefficients summing to 0.989. Lending intensity exerts a significant negative contemporaneous effect, followed by a delayed positive reversal, indicating maturity transformation risk. HAC-robust standard errors confirm the significance of lending intensity and liquidity persistence under heteroskedasticity. Breusch-Godfrey tests confirm the absence of serial correlation at any lag. These findings underscore the importance of disciplined asset–liability management and stable funding structures for enhancing liquidity resilience in Sri Lanka's banking sector.

Keywords: *Lending Intensity; Funding Composition; Liquidity Risk Persistence; Commercial Banks; ARDL*

1. Introduction

Liquidity risk has emerged as a central concern in the governance and stability of commercial banking systems globally. The fundamental nature of banking, transforming short-term liabilities into longer-term assets, inherently exposes financial institutions to funding pressures and rollover risk. The global financial crisis of 2007–2009 demonstrated that even adequately capitalised banks can encounter severe stress when liquidity management is inadequate, prompting regulators and researchers alike to prioritise the study of asset–liability dynamics as a determinant of liquidity resilience (Bonner et al., 2015; Sharma, 2023). In response, the Basel Committee on Banking Supervision introduced the Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR) under the Basel III framework to promote sound liquidity risk management across jurisdictions.

In emerging economies, the challenge is compounded by heightened macroeconomic volatility, shallow capital markets, and a heavy dependence on bank-based financial intermediation. Sri Lanka represents a particularly relevant case: the country's licensed commercial banks dominate financial intermediation, operating under evolving regulatory requirements while navigating significant economic fluctuations, including the severe economic crisis of 2021–2022. Balance-sheet characteristics such as lending intensity, reliance on non-deposit borrowing, and credit growth trajectories, therefore, play a decisive role in determining liquidity outcomes (Shafana, 2024; Samarasinghe & Lakmal, 2025). Despite a growing international literature on bank liquidity risk, empirical evidence for Sri Lanka remains limited and fragmented. Existing studies predominantly employ cross-sectional or static panel approaches using annual data, which may obscure the short-run dynamics and adjustment lags critical to understanding liquidity behaviour (Inshira & Jahfer, 2018). Little attention has been devoted to distinguishing between transitory liquidity shocks and persistent structural vulnerabilities arising from the asset–liability structure itself.

This paper addresses the gap by examining the dynamic effects of lending intensity and funding composition on liquidity risk persistence in Sri Lankan licensed commercial banks, using monthly balance sheet data spanning December 1995 to November 2024 and an autoregressive distributed lag framework. The ARDL approach is particularly appropriate because it accommodates the persistence of liquidity conditions, allows distributed lag effects of explanatory variables, and does not require variables to be integrated of the same order (Pesaran et al., 2001). The study makes several contributions to the literature. First, it provides high-frequency empirical evidence on liquidity risk dynamics in Sri Lanka using 347 monthly observations, a context underrepresented in the banking literature. Second, it models the dynamic, multi-period effects of key asset liability variables, capturing both immediate and delayed liquidity impacts.

2. Literature Review

Liquidity risk in banking is theoretically grounded in the maturity transformation function of financial intermediaries. Banks borrow short and lend long, generating a structural mismatch between the maturity of assets and liabilities. Diamond and Dybvig (1983) formalised this vulnerability by demonstrating that banks are inherently susceptible to self-fulfilling runs when depositors anticipate insolvency. Subsequent theoretical developments have emphasised the role of funding composition, balance-sheet structure, and market liquidity in shaping systemic vulnerability (Brunnermeier & Pedersen, 2009). Asset–liability management (ALM) theory addresses this vulnerability by advocating for the dynamic alignment of asset and liability cash flows. Rutkauskas and Stankeviciene (2006) conceptualise ALM as an integrated portfolio management approach that simultaneously optimises liquidity and profitability. More recent frameworks incorporate regulatory dimensions, highlighting how Basel III liquidity standards reshape the ALM decisions of individual institutions (Huang, 2025). Theoretical models further distinguish between funding liquidity risk, the inability to roll over short-term liabilities, and market liquidity risk, the inability to liquidate assets without large price concessions. Both dimensions interact in times of stress, amplifying systemic fragility (Bai et al., 2017).

Empirical research on the determinants of bank liquidity risk consistently identifies the loan-to-deposit ratio, non-performing loan ratio, and capital adequacy ratio as key explanatory variables. Inshira and Jahfer (2018) examine Sri Lankan domestic licensed commercial banks and find that asset–liability management factors significantly influence liquidity risk. Maduwanthi and Morawakage (2019) extend this analysis to systemically important banks in Sri Lanka, documenting that the liquidity gap and non-performing loans negatively affect return on assets and return on equity. Samarasinghe and Lakmal (2025) provide more recent evidence using panel data from 2011 to 2021, finding that the non-performing loan ratio and loan-to-deposit ratio negatively affect financial performance. Shafana (2024) evaluates the efficacy of risk management practices in Sri Lankan financial institutions and finds that inadequate liquidity management reduces profitability and operational stability. In the broader international literature, Sundaresan and Xiao (2024) find that quantity-based liquidity rules reduce liquidity risk but may crowd out lending. Hou and Yang (2024) demonstrate that digital transformation reduces structural liquidity gaps in Chinese banks.

The dominant methodological approach in the Sri Lankan context relies on cross-sectional panel data regression using annual frequency data. While informative, this approach is limited in its ability to capture the dynamic, high-frequency adjustments in liquidity conditions that characterise banking behaviour. Time-series approaches remain underutilised in the Sri Lankan context. The ARDL model, introduced by Pesaran et al. (2001), offers several advantages: it accommodates variables of mixed integration orders, captures persistence and distributed lag effects, and is suitable for moderate sample sizes. Applications in banking research have demonstrated its value in capturing adjustment dynamics that static models cannot (Sharma, 2023; Ayub et al., 2024).

3. Data and Methodology

3.1. Data

The study uses monthly aggregate balance sheet data sourced from the Central Bank of Sri Lanka (CBSL) statistical publications. The dataset spans December 1995 to November 2024, yielding 347 usable observations after accounting for the 12-month lag required for the year-on-year loan growth variable and the two autoregressive lags in the augmented Dickey-Fuller (ARDL) specification. Liquidity risk is proxied by the ratio of liquid assets to total assets, where liquid assets comprise cash on hand, balances due from the Central Bank, Treasury Bills, Treasury Bonds, other government securities, and other investments. Note that this ratio is a liquidity buffer indicator: higher values reflect greater liquidity capacity and lower exposure to funding stress, while a declining ratio signals increasing liquidity risk. This inverse relationship is maintained throughout the interpretation of results. The measure is consistent with the banking liquidity literature and prior Sri Lankan studies (Inshira & Jahfer, 2018; Samarasinghe & Lakmal, 2025).

Three key explanatory variables capture core asset–liability dynamics. The loan-to-deposit ratio (LDR) measures lending intensity, the extent to which deposit funding supports credit creation. Borrowing dependence (BD) captures the ratio of total non-deposit borrowings (domestic interbank and foreign borrowings) to total assets, reflecting reliance on volatile market-based funding. Year-on-year loan growth (YoY) serves as a control variable, computed as the 12-month percentage change in total loans and advances, reflecting credit expansion pressure and its potential liquidity impact.

Table 1. *Variable Definitions and Sources*

Variable	Definition	Source
Liquidity Risk (LR)	Liquid assets ÷ Total assets (%)	CBSL data
Loan-to-Deposit Ratio (LDR)	Total loans ÷ Total deposits (%)	CBSL data
Borrowing Dependence (BD)	Total borrowings ÷ Total assets (%)	CBSL data
YoY Loan Growth	12-month % change in total loans	CBSL data

3.2. Econometric Framework

To model the dynamic relationship between asset–liability structure and liquidity risk, the study employs an autoregressive distributed lag (ARDL) model. The general ARDL(p, q1, q2, q3) specification is:

$$\mathrm{LR}_t = \alpha + \sum_{i=1}^{p} \phi_i \mathrm{LR}_{t-i} + \sum_{j=0}^{q_1} \beta_j \mathrm{LDR}_{t-j} + \sum_{k=0}^{q_2} \gamma_k \mathrm{BD}_{t-k} + \sum_{\ell=0}^{q_3} \delta_\ell \mathrm{LG}_{t-\ell} + \varepsilon_t. \tag{1}$$

where LR denotes liquidity risk, LDR the loan-to-deposit ratio, BD borrowing dependence, LG year-on-year loan growth, and ε an error term. The optimal lag structure ARDL(2,2,1,2) is selected using the Akaike Information Criterion (AIC). The model is estimated in R using the ARDL package (Natsiopoulos

& Tzeremes, 2022).

Pre-estimation tests include the ADF unit root tests to confirm the integration orders of all variables. The Pesaran et al. (2001) bounds F-test is applied to assess the presence of a long-run cointegrating relationship. Post-estimation diagnostics include the Breusch-Godfrey LM test for serial correlation, the Breusch-Pagan test for heteroskedasticity, the Jarque-Bera test for residual normality, and the CUSUM test for parameter stability. Where heteroskedasticity is detected, HAC (Newey-West) robust standard errors are reported. The Zivot-Andrews test is applied to each variable to test for structural breaks in the individual series. The full-sample ARDL is retained as the primary specification because the objective of the study is to characterise the average short-run adjustment dynamics across the full history of Sri Lanka's commercial banking sector; the CUSUM test is applied diagnostically to identify and interpret parameter evolution rather than to invalidate the full-sample estimates. Sub-period analysis is suggested as a direction for future research.

4. Results and Discussion

4.1. Unit Root Tests

Table 2 reports the results of the ADF unit root tests with intercept and AIC lag selection, applied to both levels and first differences of all variables.

Table 2. *ADF Unit Root Test Results*

Variable	**ADF (levels)**	**ADF (1st diff)**	**Lags**	**CV 5%**	
Liquidity Risk	0.3198	−12.4877***	1	−2.87	I(1)
Loan-to-Deposit Ratio	−0.5961	−11.1878***	1	−2.87	I(1)
Borrowing Dependence	−1.7923	−14.5892***	1	−2.87	I(1)
YoY Loan Growth	−2.3574	−9.7497***	1	−2.87	I(1)

Note. *** $p < 0.01$. ADF with intercept (drift), AIC lag selection. Critical value −2.87 at 5% (MacKinnon). All variables are non-stationary at levels and stationary at first differences, confirming I(1). No variable is I(2), validating the ARDL approach.

All four variables are non-stationary at levels but stationary at first differences, confirming an order-one integration. Importantly, no variable is I(2), which is a prerequisite for the validity of the ARDL bounds testing approach (Pesaran et al., 2001). The Zivot-Andrews structural break test (Table 3) further confirms that the unit root in each variable is not attributable to a structural break.

Table 3. *Zivot-Andrews Structural Break Test*

Variable	**ZA Statistic**	**CV 5%**	**Break (obs)**
Liquidity Risk	−3.335	−5.08	302 (~Oct 2020)
Loan-to-Deposit Ratio	−2.988	−5.08	282 (~Feb 2019)
Borrowing Dependence	−3.948	−5.08	295 (~Mar 2020)
YoY Loan Growth	−3.442	−5.08	80 (~Aug 2002)

4.2. ARDL Model Estimation and Bounds Test

Table 4 reports the ARDL(2,2,1,2) estimation results using both OLS and HAC (Newey-West) robust standard errors. The Breusch-Pagan test detects heteroskedasticity (BP = 24.724, p = 0.006), making HAC-robust inference the preferred basis for hypothesis testing. The model achieves an R^2 of 0.985; however, this high fit primarily reflects the strong autoregressive persistence of the dependent variable (AR sum ≈ 0.989) rather than the explanatory contribution of the regressors, and should not be over-interpreted as evidence of model quality.

Table 4. *ARDL(2,2,1,2) Estimation Results*

Variable	OLS Coef.	OLS SE	HAC SE	HAC t	p-value
Constant	0.690	0.718	0.744	0.928	0.354
LiqRisk (L1)	0.730***	0.053	0.085	8.568	< 0.001***
LiqRisk (L2)	0.258***	0.053	0.084	3.070	0.002**
LDR (L0)	−0.280***	0.050	0.060	−4.651	< 0.001***
LDR (L1)	0.203***	0.063	0.061	3.346	< 0.001***
LDR (L2)	0.079	0.052	0.064	1.239	0.216
BorrowDep (L0)	−0.159	0.102	0.119	−1.343	0.180
BorrowDep (L1)	0.092	0.101	0.121	0.760	0.448
YOY (L0)	1.542	2.714	3.546	0.435	0.664
YOY (L1)	3.070	4.005	4.542	0.676	0.500
YOY (L2)	−5.449	2.794	3.206	−1.700	0.090.

Note. *** $p < 0.01$; ** $p < 0.05$; . $p < 0.10$. N = 345. $R^2 = 0.985$. HAC = Newey-West robust standard errors reported due to detected heteroskedasticity (BP = 24.724, $p = 0.006$). Estimated using the ARDL package in R.

The bounds cointegration F-test yields F = 0.923 (p = 0.924), falling well below the lower-bound critical value of 3.62 at the 5% significance level (Pesaran et al., 2001, Case II). The null hypothesis of no cointegration cannot be rejected, indicating that a stable long-run equilibrium relationship between liquidity risk and the asset–liability variables is not confirmed over the full sample. Consequently, no long-run level coefficients are estimated or reported; the bounds test framework requires confirmed cointegration before a long-run equation can be validly interpreted (Pesaran et al., 2001). The result is consistent with the CUSUM parameter stability test (Section 4.4), which identifies significant structural change over the sample period: the bounds test is sensitive to such instability, and the failure to confirm cointegration is best understood as reflecting the evolving nature of the relationship across distinct macroeconomic and regulatory regimes rather than its permanent absence. The study, therefore, limits inference to the short-run dynamic relationships, for which HAC-robust estimates are reported.

4.3. Short-Run Dynamics

The persistence of liquidity risk is confirmed by the large, statistically significant coefficients on both autoregressive terms under HAC-robust inference. The first-order lag coefficient of 0.730 (t = 8.568, p < 0.001) and second-order lag of 0.258 (t = 3.070, p = 0.002) together imply an AR sum of approximately 0.989, indicating that nearly all liquidity shocks persist into the following period before gradual dissipation. This high degree of persistence is consistent with the presence of balance-sheet adjustment costs and funding rigidities (Sharma, 2023; Mashamba & Kwenda, 2017).

The loan-to-deposit ratio exhibits a significant negative contemporaneous effect ($\beta = -0.280$, HAC t = −4.651, p < 0.001) and a significant positive lagged effect at L1 ($\beta = 0.203$, HAC t = 3.346, p < 0.001).

Recalling that the dependent variable is the liquid-assets-to-total-assets ratio — a buffer measure — this negative contemporaneous effect indicates that an increase in lending intensity immediately compresses the liquidity buffer, as loan disbursements convert liquid assets into illiquid claims. The partial positive reversal at L1 suggests that subsequent inflows of deposit or borrowed funds partially replenish the buffer in the following period, though the net cumulative effect remains negative given the smaller magnitude of the L1 coefficient. The L2 coefficient (0.079) is not significant under HAC standard errors (p = 0.216). Borrowing dependence and YoY loan growth are not statistically significant under HAC-robust inference, with all p-values exceeding 0.10. While the contemporaneous and lagged YoY coefficients approach marginal significance at L2 (HAC t = −1.700, p = 0.090), the evidence is insufficient to draw strong inferences. This result differs from initial OLS estimates and highlights the importance of applying heteroskedasticity-robust inference in time-series banking data.

4.4. Diagnostic Tests

Table 5 summarises all post-estimation diagnostic test results.

Table 5. *Post-Estimation Diagnostic Tests*

Test	Statistic	p-value
Bounds F-test (cointegration)	F = 0.923	0.924
Breusch-Godfrey LM (lag 1)	LM = 1.332	0.249
Breusch-Godfrey LM (lag 4)	LM = 5.454	0.244
Breusch-Godfrey LM (lag 12)	LM = 14.068	0.296
Breusch-Pagan (heteroskedasticity)	BP = 24.724	0.006
Jarque-Bera (normality)	χ^2 = 174.03	< 0.001
CUSUM (parameter stability)	S = 5.560	< 0.001

Serial correlation is absent at all lag lengths tested (lags 1, 4, and 12), confirming that the ARDL specification adequately captures the data's dynamic structure. Heteroskedasticity is present (BP = 24.724, p = 0.006), addressed by reporting HAC-robust standard errors as the primary inferential basis. Residuals are non-normal (JB = 174.03, p < 0.001), reflecting skewness and excess kurtosis; however, with T = 347, the Central Limit Theorem ensures that coefficient estimates and t-statistics remain asymptotically valid.

(Note: Red lines indicate 5% significance boundaries.)

The CUSUM test (Figure 1) (S = 5.560, p < 0.001) indicates significant parameter instability over the full sample, with the CUSUM statistic crossing below the lower boundary from approximately observation 35 onwards and recovering toward the boundary from approximately observation 277 onwards. This finding suggests that the relationship between lending intensity, funding composition, and liquidity risk persistence has evolved over the sample period, consistent with the post-conflict economic expansion from 2009, the phased introduction of Basel III regulatory requirements, and the severe economic crisis of 2021–2022. This structural evolution explains the failure of the bounds cointegration test and represents an important contextual finding in its own right.

4.5. Discussion

The results reveal a clear and robust finding: liquidity risk in Sri Lankan licensed commercial banks is highly persistent, with AR coefficients summing to 0.989 under HAC-robust inference. This persistence implies that liquidity shocks are not quickly absorbed but instead propagate forward across multiple periods, consistent with balance-sheet adjustment costs and funding rigidities inherent in emerging-market banking systems. The loan-to-deposit ratio emerges as the primary significant determinant of short-run

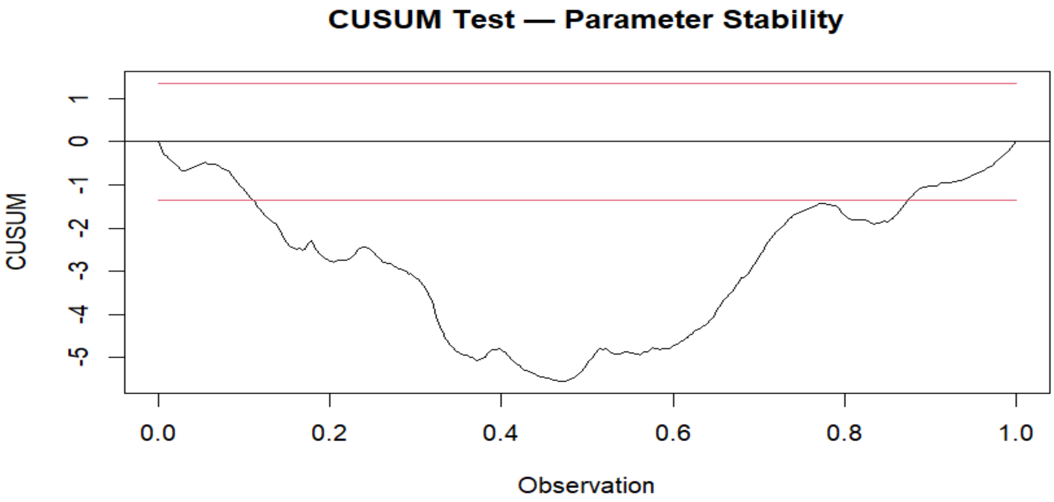

Figure 1. *CUSUM Test for Parameter Stability.*

liquidity risk under robust inference. The pattern of a negative contemporaneous effect followed by a positive reversal at L1 captures the dynamic sequence of maturity transformation risk: an initial period where rising LDR is associated with temporary liquidity improvement, followed by a deterioration as funding pressures materialise. This finding is broadly consistent with prior Sri Lankan evidence (Inshira & Jahfer, 2018; Maduwanthi & Morawakage, 2019) while providing additional temporal resolution through the monthly framework. The parameter instability identified by the CUSUM test is an important substantive finding. It indicates that the quantitative relationship between asset–liability variables and liquidity risk is not fixed over time but evolves in response to macroeconomic and regulatory changes. This has direct implications for supervisory monitoring: static regulatory thresholds may become miscalibrated as the structural relationship shifts, suggesting the need for dynamic, adaptive approaches to liquidity risk oversight in Sri Lanka.

5. Conclusion

This study provides time-series evidence on the short-run dynamic relationship between asset–liability structure and liquidity risk in Sri Lankan licensed commercial banks, using 347 monthly observations and an ARDL(2,2,1,2) framework estimated with HAC-robust standard errors. Unit root tests confirm all variables are I(1), validating the ARDL approach. The bounds cointegration test does not confirm a stable long-run relationship over the full sample, a result attributed to parameter instability identified by the CUSUM test and reflecting structural changes in Sri Lanka's banking environment over the sample period. Short-run results reveal highly persistent liquidity risk (AR sum $\approx$ 0.989) and a significant dynamic effect of lending intensity. The loan-to-deposit ratio exerts a negative contemporaneous effect followed by a positive reversal, capturing the delayed materialisation of maturity transformation risk. Serial correlation is absent at all lags tested, confirming adequate model specification. The findings carry clear implications for banking regulation and risk management. The persistence of liquidity risk suggests that supervisory monitoring should be forward-looking, recognising that current liquidity conditions strongly predict future conditions. The significance of lending intensity under robust inference underscores the importance of maintaining sustainable loan-to-deposit ratios as a first line of defence against liquidity risks. The CUSUM instability finding argues for periodic recalibration of liquidity risk models to account for structural changes in the banking environment. Future research should incorporate bank-level data to examine heterogeneity across institutions, extend the framework to include macroeconomic variables such as interest rates and GDP growth, and explore the post-2022 recovery period as a distinct structural regime. The integration of digital transformation indicators into the liquidity risk framework also represents a promising direction for the Sri Lankan banking literature.

References

Ayub, R., Alhabshi, S. M., & Othman, A. H. A. (2024). Basel III liquidity regulations and financial intermediation in Pakistan. In Banking regulation and financial stability. Springer. https://doi.org/10.1007/978-3-031-54009-7_15

Bai, J., Krishnamurthy, A., & Weymuller, C. (2017). Measuring liquidity mismatch in the banking sector. Social Science Research Network. https://doi.org/10.2139/SSRN.2343043

Bonner, C., van Lelyveld, I., & Zymek, R. (2015). Banks' liquidity buffers and the role of liquidity regulation. Journal of Financial Services Research, 48(3), 215–234.

Brunnermeier, M. K., & Pedersen, L. H. (2009). Market liquidity and funding liquidity. The Review of Financial Studies, 22(6), 2201–2238.

Diamond, D. W., & Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. Journal of Political Economy, 91(3), 401–419.

Fei, R. (2007). A stochastic programming model of domestic commercial bank asset and liability management based on liquidity risk constraints. Mathematics in Practice and Theory.

Hlebik, S. (2017). Liquidity risk under the new Basel global regulatory framework. Applied Economics and Finance, 4(6), 78–90.

Hou, X., & Yang, R. (2024). Bank digital transformation and liquidity mismatch: Evidence from China. https://doi.org/10.1016/j.iref.2024.02.050

Huang, Z. (2025). How commercial banks manage risks through liquidity governance. Journal of Economic Insights, 2(2), 44–51.

Inshira, M. J. F., & Jahfer, A. (2018). The effect of asset liability management on the liquidity risk of domestic licensed commercial banks in Sri Lanka.

Maduwanthi, R., & Morawakage, P. (2019). Impact of liquidity risk on the performances of Sri Lankan commercial banks. https://doi.org/10.4038/SLJSS.V42I1.7572

Mashamba, T., & Kwenda, F. (2017). A look at the liquidity management practices of banks in South Africa. Journal of Economics and Behavioral Studies, 9(3), 113–120.

Natsiopoulos, K., & Tzeremes, N. G. (2022). ARDL bounds test for cointegration: Replicating the Pesaran et al. (2001) results for the UK earnings equation using R. Journal of Applied Econometrics, 37(5), 1079–1090.

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics, 16(3), 289–326.

Rutkauskas, A. V., & Stankeviciene, J. (2006). Integrated asset and liability portfolio as instrument of liquidity management in the commercial bank. https://doi.org/10.3846/16111699.2006.9636123

Samarasinghe, S. L. G. M. M., & Lakmal, W. A. I. (2025). The impact of liquidity risk on the financial performance of licensed commercial banks in Sri Lanka. Sri Lankan Journal of Banking and Finance, 7(2), 35–48.

Shafana, M. A. C. N. (2024). Evaluating the efficacy of risk management practices and their necessity for enhancing the profitability of financial institutions in Sri Lanka. Asian Journal of Economics, Business and Accounting, 24(8).

Sharma, R. (2023). Liquidity risk and bank performance: Evidence from emerging markets. Journal of Banking and Finance Research.

Sundaresan, S., & Xiao, K. (2024). Liquidity regulation and banks: Theory and evidence. Journal of Financial Economics. https://doi.org/10.1016/j.jfineco.2023.103747

Yang, Z., & Xu, W. (2009). Optimal model of assets and liabilities management considering interest risk and time structure risk. https://doi.org/10.1109/ICISE.2009.806

Zivot, E., & Andrews, D. W. K. (1992). Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. Journal of Business & Economic Statistics, 10(3), 251–270.